

Estimation of Separation Buffers for Wind-Prediction Error in an Airborne Separation Assistance System

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Abstract Wind prediction errors are known to affect the performance of automated air traffic management tools that rely on aircraft trajectory predictions. In particular, automated separation assurance tools, planned as part of the NextGen concept of operations, must be designed to account and compensate for the impact of wind prediction errors and other system uncertainties. In this paper we describe a high fidelity batch simulation study designed to estimate the separation distance required to compensate for the effects of wind-prediction errors throughout increasing traffic density on an airborne separation assistance system. These experimental runs are part of the Safety Performance of Airborne Separation experiment suite that examines the safety implications of prediction errors and system uncertainties on airborne separation assurance systems. In this experiment, wind-prediction errors were varied between zero and forty knots while traffic density was increased several times current traffic levels. In order to accurately measure the full unmitigated impact of wind-prediction errors, no uncertainty buffers were added to the separation minima. The goal of the study was to measure the impact of wind-prediction errors in order to estimate the additional separation buffers necessary to preserve separation and to provide a baseline for future analyses. Buffer estimations from this study will be used and verified in upcoming safety evaluation experiments under similar simulation conditions. Results suggest that the strategic airborne separation functions exercised in this experiment can sustain wind prediction errors up to 40kts at current day air traffic density with no additional separation distance buffer and at eight times the current day with no more than a 60% increase in separation distance buffer.

Keywords-component; *Air Traffic Management; Conflict Detection and Resolution; Airborne Separation; ASAS; Safety; Wind-prediction Errors;*

I. INTRODUCTION

Assessing the safety effects of prediction errors and uncertainty on automation-supported functions in the Next Generation Air Transportation System [1] concept of operations is of foremost importance, particularly safety critical functions such as separation that involve human decision-making, both ground-based and airborne. The automation of separation functions must be designed to account for, and mitigate the impact of, information uncertainty and varying human response [2]. Wind-prediction errors are known to affect the performance of trajectory prediction tools and ground

based conflict probes [3, 4]. While the accuracy of wind field forecasts has improved in recent years and has been proven to be satisfactory for most applications it is known that occasional large errors can occur with potentially unacceptable impact to safety critical applications. For that reason, it is important to conduct extensive laboratory experiments to understand such effects and to develop and validate the necessary mitigation strategies to maintain safety standards.

This study is part of a series of experiments that comprises batch simulation studies investigating the safety impact of prediction errors and system uncertainties on Airborne Separation Assistance Systems (ASAS) applications. The scenarios used in these experiments consist of randomized routes in a generic high-density airspace in which all aircraft are constrained to the same flight level. Sustained average traffic density is varied from 11.2 to 21.4 aircraft per 10K nmi², approximating up to about 12.5 times today's traffic density in a similarly sized en route sector. Two previous experiments utilizing the same simulation platform have been conducted so far. Results from the first baseline study indicate that at five times the typical traffic density of today's National Airspace System (NAS) and under the assumptions of the study, airborne separation can be safely performed [5]. In the second study, pilot actions required by the ASAS automation to resolve traffic conflicts were varied over a wide range of response times, varying from 5 to 240 seconds. Results indicate that the strategic ASAS functions exercised in the experiment can sustain pilot response delays of up to 90 seconds and more, depending on the traffic density [2].

The current study focuses on wind-prediction errors which are known to have a detrimental effect on the ability of automated trajectory prediction tools, which in turn affects the performance of both cockpit and ground based decision support tools that rely on accurate predictions. In this experiment wind-prediction errors were varied from 0 to 40 kts while traffic density was increased from five to 21 aircraft per 10K nmi². Aircraft separation was set to the standard five nmi for en route airspace and no mitigation technique is used to compensate for the position uncertainty of the aircraft. The goal of the experiment was to measure the magnitude of the separation violations to determine the appropriate separation distance required to preserve safe separation. The resulting buffer estimations will be evaluated as part of subsequent research activities.

This paper is organized as follows: Section II presents a brief summary of previous work, Section III describes the simulation platform, and Sections IV through VII describes the experiment design and results. Finally, Section VIII presents conclusions and future research directions.

II. BACKGROUND

Integrated air/ground operational concepts have been proposed in which some aircraft crews exercise separation functions aided by ASAS tools on the flight deck, while air traffic controllers exercise ground based separation control for non-ASAS-equipped aircraft and terminal operations [6] often supported by various decision support tools. These decision aids rely on broadcast data-linked information that includes aircraft velocity vectors and limited flight plan information through a surveillance capability such as the Automatic Dependent Surveillance – Broadcast (ADS-B) [7]. The automation is designed to detect conflicts between aircraft and generate conflict resolution routes and conflict-free maneuvering advisories [8, 9] by building predictions of aircraft trajectories. One of the major difficulties associated with aircraft trajectory predictions are the assumptions that must be made regarding environmental conditions, aircraft dynamics, communication reliability and human operator's performance. These assumptions introduce different degrees of uncertainties that must be accounted for by any automated system used in safety critical applications. Until now, safety evaluation of Separation Assurance (SA) applications has, for the most part, been based on studies using simulation tools that seldom include models of system uncertainties [10,11,12] and often make many simplifying assumptions such as perfect navigation performance and absence of prediction errors or off-nominal conditions.

The effects of uncertainty on the performance of an automated conflict detection and resolution system were the focus of a recent experiment that studied uncertainty factors associated mostly with ground based modeling technology such as climb and descent speed profile, aircraft weight, and flight plan route intent. A more recent study [13] used an eight nmi separation for conflict detection and a 10 nmi separation for conflict resolution, for aircraft in level flight, to mitigate for uncertainties. Results pointed at key modeling issues such as climb trajectory prediction uncertainty or aircraft intent.

The Safety Performance of Airborne Separation (SPAS) simulation suite of studies attempts to characterize and quantify the safety performance of ASAS applications using a simulation platform that includes high fidelity models of aircraft dynamics, flight management system, data-link communications, and conflict detection and resolution functions as described in the next section. The baseline set of runs for the SPAS experiment, completed in the spring of 2007, included scenarios with no system uncertainties or prediction errors [5]. Results from that study indicated that within the experimental conditions and assumptions, safety was preserved with no losses of separation observed for traffic densities much higher than current levels. For the baseline SPAS test runs described in the aforementioned study, ADS-B reception was perfect (i.e., all messages received at all ranges), full aircraft trajectory intent was shared, the pilot responded correctly to all

traffic alerts with no delays, and wind-predictions were accurate. Results showed that at five times the typical traffic density of today's NAS, utilizing only airborne intent based, strategic conflict detection and resolution logic with a 10-minute look-ahead time, safe separation of aircraft can be maintained under the assumptions and conditions of the test.

A second SPAS study [2] investigated the effects of human operator inattentiveness when interacting with cockpit based automated systems used for separation assistance. These effects were observed by varying pilot delays and responsiveness within wide ranges. Loss of Separation (LOS) count and resolution to First Loss of Separation (FLOS) time were evaluated to assess the performance of the system under the experimental conditions. An in-depth analysis of the underlying causes for the observed behavior revealed great stability of the airborne strategic resolution capability under a large range of conditions.

Wind-prediction errors are known to affect the performance of trajectory prediction tools and ground based air traffic management tools. While the accuracy of wind field forecasts has improved in recent years it is still the case that large errors can occur, potentially impacting the performance of safety critical applications. The improved quality and increased availability of the new Rapid Update Cycle (RUC-2) wind forecasts are shown [14] to significantly benefit air traffic management applications. A later study [15] investigated sources of wind forecast error differences between Rapid Update Cycle, version 1 (RUC-1), and the newer RUC-2. The study confirmed the previous work by demonstrating measured improvement on wind forecast quality and availability. The study also quantified the percentage of large infrequent vector errors was reduced which was shown to be 3% overall and 7% during peak months. "Such peak error periods have a strong impact on air traffic management automation tools particularly if they persist along a predicted trajectory for 20 min or more. A 15-kt mean error in the along-track wind component over a 20 min trajectory prediction for an aircraft will result in a 5 nmi position error." [15] Two flight tests were conducted to evaluate the effects of multiple sources of errors on the trajectory prediction accuracy of both ground-based and airborne automation systems. [3] The main source of error for the ground based systems was found to be the predicted winds aloft. In fact, the wind error at cruise approached 80 knots for several runs. Results from these tests revealed the occasional existence of "large" errors in the predicted wind field (greater than 20 knots) that span multiple sectors for periods greater than several hours at a time. A more recent study [4] investigated the User Request Evaluation Tool's (URET) prediction sensitivity to weather forecast error by altering RUC-2 weather forecast adding 20 or 60 knots to the wind magnitude, 45 or 90 degrees to the wind direction. A comparative statistical analysis provided evidence that the forecast errors in wind magnitude and direction had significant effect on the longitudinal trajectory error and a modest impact on retracted false alerts relative to controlled baseline URET runs with no errors.

III. THE SIMULATION PLATFORM

The simulation runs described herein were conducted in the Air Traffic Operations Laboratory (ATOL) at NASA Langley Research Center utilizing a distributed simulation platform that includes a cluster of aircraft simulators interconnected through a High Level Architecture communication and simulation infrastructure known as the Airspace & Traffic Operations Simulation (ATOS) [16] depicted in Fig. 1

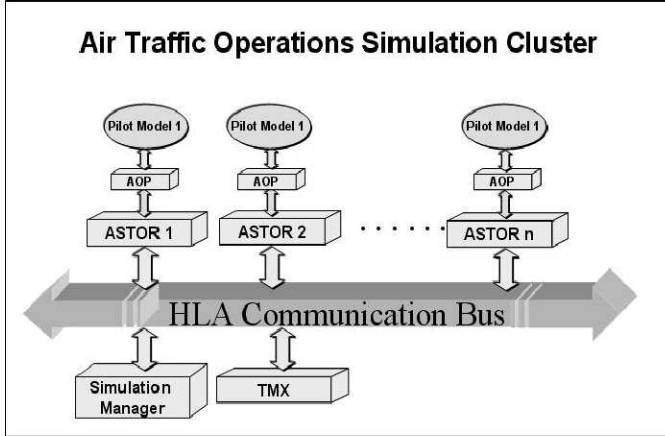


Figure 1. Airspace and Traffic Operations Simulation Platform

The ATOS batch platform is comprised of hundreds of real-time aircraft simulators equipped with high fidelity, six degree-of-freedom dynamic airplane model, a Flight Management System (FMS), Mode-S ADS-B data-link capability, and a prototype airborne conflict management system called the Autonomous Operations Planner (AOP). Conceptually, the ATOS batch simulation platform is a multi-agent system composed of multiple distributed autonomous software agents modeling ASAS equipped aircraft flown by a pilot model. A rule-based pilot model was developed to “fly” the simulators and perform the basic pilot actions required to interact with the airborne conflict management system. In the current study, the pilot model was configured to react to all conflict alerts by requesting a resolution trajectory from AOP [8] and accepting it. The pilot model was also configured with a mean delay time and standard deviation of 500 and 1.5 milliseconds, respectively. These were the same values used in the initial baseline SPAS experiment [5].

The AOP [8], a NASA-developed research ASAS prototype was built for the study of advanced distributed air-ground air traffic management concepts. The intent-based conflict detection (CD) function of AOP uses state and intent data received from other traffic aircraft over ADS-B in combination with ownship state data, auto-flight mode settings, and flight plan information to deterministically predict future losses of separation. AOP also has a second, independent, CD system that uses state-vector projections to detect flight crew blunders and prediction faults of the intent-based CD system and other short time horizon conflicts. Conflict alerting is modeled after the multi-alert-level approach recommended by RTCA [17]. For conflict resolution (CR), AOP contains both strategic and tactical capabilities. Tactical CR refers to open-loop vectors or altitude changes to solve conflicts with no predetermined

reconnection to the original trajectory. Strategic CR refers to the single action of modifying the flight plan such that the conflict is solved and the aircraft reconnects to the previous trajectory. The strategic resolution logic attempts to find a route that both conforms to a Required Time of Arrival (RTA) and is conflict-free for 20 minutes. Nominal look-ahead time is 10 minutes, but the strategic CR will attempt resolutions with as little as two minutes to loss of separation (LOS). If a resolution is found, it is guaranteed to preserve separation in the absence of prediction errors, even if only one aircraft executes it. If a strategic resolution cannot be found in time, the system would normally transition to a tactical resolution phase (typically at three minutes to LOS), which was not present in this experiment. The result of not having the tactical back-up system is that conflicts irresolvable by the strategic system of both aircraft will result in separation loss. AOP also includes functions for conflict prevention, including at-a-glance maneuver restriction symbology for the flight crew and support for tactical / strategic trajectory probing (also known as provisional CD). These functions were not required for this study and were therefore disabled.

IV. EXPERIMENT DESCRIPTION

A. Goals of the Study

The goal of this experiment was to determine an appropriate separation distance that will preserve safe separation in the presence of wind-prediction errors over an increasing range of air traffic densities.

To determine this value, it was necessary to calculate the magnitude of separation violations in a series of simulations with varying wind-prediction errors over an increasing airspace density. This was accomplished by measuring the distance at the closest point of approach (CPA) between all aircraft in the simulation. This distance will be used as a predictor of buffer size in future experiments. In the current study, wind-prediction errors were varied from 0 to 40 kts and no mitigation technique was used to compensate for the position uncertainty of the surrounding aircraft. This CPA measure will provide a conservative (larger than required) estimate of the separation buffers given that the conditions of the experiment do not include tactical conflict resolutions.

B. Experiment Scenarios and Assumptions

The test region, representing a notional en route airspace sector is modeled as a circular area with a diameter of 160 nmi. The test region is surrounded by an initialization region, the outer boundary of which is the location where aircraft are initialized in the simulation. This initialization method provides each aircraft’s AOP with a full 10-minute look-ahead time for detecting conflicts that occur within the test region. Aircraft are generated at random points on the outer circle initially with straight trajectories that traverse the test region at random angles and continue to a waypoint with a required time of arrival. An RTA constraint is placed outside the test area to force strategic conflict resolutions to comply with it, as an additional element of complexity. All aircraft in the simulation are ASAS equipped and fly at the same altitude so as to constrain the scenarios to lateral conflict resolutions only and

to achieve higher traffic densities. For this study, the auto-flight system remained coupled to the FMS for lateral navigation such that there was no tactical maneuvering. No altitude changes were permitted. There were no communication errors or ADS-B message degradation due to signal range or interference. More details on the scenario design can be found in the Preliminary SPAS experiment report [5]. ADS-B communications included full intent data. A priority rule (i.e., right of way) system was in effect that prevented undesirable synchronicity of resolution maneuvers by both aircraft involved in a conflict. Aircraft given priority for a given conflict had their alerts delayed 3 minutes while the other conflicting aircraft were alerted immediately. In Fig. 2, aircraft B has an initial trajectory that is in a conflict with aircraft A, just entering the initialization zone. Aircraft B resolves the conflict by modifying its fly path as shown in the diagram.

The state-based CD and the tactical CR capability were disabled to allow the current study to focus on strategic conflict management.

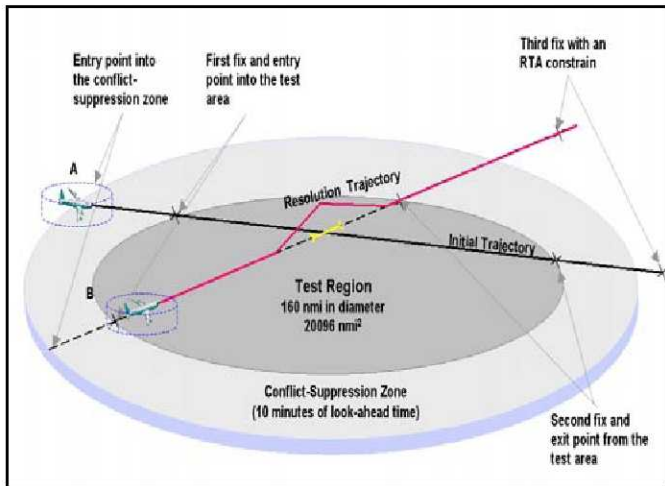


Figure 2. Experiment Test Region

C. Experimental Conditions

A two-factor experimental matrix was designed in which the average traffic density was assigned four levels and the wind-prediction error was assigned five levels as shown in Table I. The four levels of traffic density tested represent a range of 3.5X to 12.5X the current traffic density levels for high altitude, en-route airspace sectors in the NAS. More details on the traffic density calculations and how they relate to current air traffic conditions can be found in [5]. The average traffic density values shown in Table I were measured as the instantaneous count of aircraft inside the test region, sampled every ten seconds and later normalized to a sector size of ten thousand nmi². The predicted wind speed and direction as well as the truth wind direction were set to zero for all test runs while the truth wind speeds were varied within a range of 0 to 40 kts. Since the aircraft expect no winds, the truth winds represent wind-prediction errors for all the test conditions.

An exploratory set of runs was also done for a single density (10) at all wind conditions in which the truth winds were set to 0 kts and the predicted wind speed was varied from

0 to 40 kts. These runs were conducted in order to test whether there is a significant difference in the ASAS algorithm performance if wind error results primarily from poor prediction in the presence of winds versus over-prediction of winds when there are no winds.

TABLE I. EXPERIMENT CONDITIONS

Traffic Density (#aircraft per 10K nmi ²)	Pred. Wind Dir. (Deg)	Predicted Wind Speed (Kts)	Truth Wind Direction (Deg)	Truth Wind Speed (Kts)				
~5	0°	0	0°	0	10	20	30	40
~10				0	10	20	30	40
~16				0	10	20	30	40
~21				0	10	20	30	40
~10	0°	0	10	20	30	40	0°	

Since aircraft routes are randomly generated and their initial headings are uniformly distributed between 0° and 360°, aircraft trajectories traverse the test region with uniformly distributed heading angles. As a result, the modeled winds impact the aircraft during the simulation from all directions imposing a uniform distribution of head/tail and cross winds.

D. Experiments Results

A total of 45 simulation runs over the 20 conditions described above were conducted. This included three replications (18 real-time simulation hours) for the ~5 and ~10 density cases in order to increase the number of conflicts to nearly the same level as for the ~16 and ~21 density cases which were run 6 hours each. Each run starts with different random seeds to assure independent replications. A total of 270 real-time simulation hours were performed, representing 5120 flight hours and 16295 unique paired conflicts. Flight hours are computed as the accumulated flight time within the test area of all the aircraft in the simulation run. Since flight hours and number of conflicts depend on the traffic density of the scenario the lower density scenarios were replicated to expand the sample size. The number of conflicts was computed as the total number of conflicts that were detected by the two aircraft involved whenever the predicted LOS would occur partially or completely inside the test region. Losses of separation (LOS) and the distance at the closest point of approach were computed during post-processing of the time-correlated aircraft states. Fig. 3 shows the normalized number of LOS for each test condition. The normalized LOS count is obtained by dividing the total number of LOS occurrences by the total flight hours at each test condition. As can be observed from this plot, both Wind-prediction Error and Traffic Density impact this value. There also appears to be a flattening of results at the extreme conditions where nearly one LOS occurs per Flight Hour. This is an artifact of the 5 nmi of separation used in the experiment.

A large number of the LOS that occurred at the highest levels of traffic density and wind prediction error was either the result of limitations in trajectory turn modeling or simulation specific artifacts derived from the scenario conditions. This

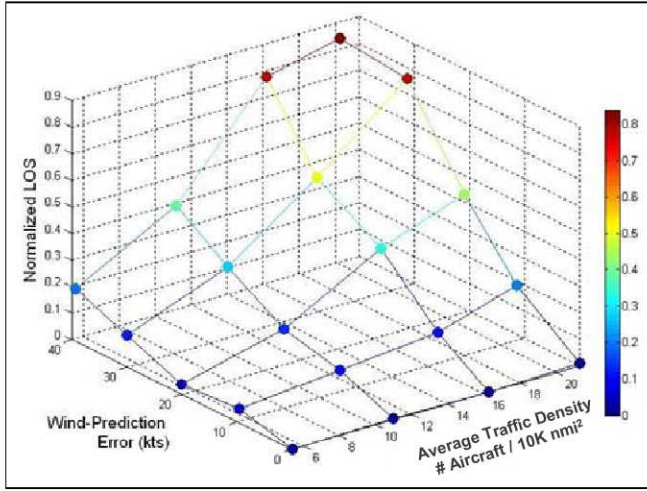


Figure 3: Normalized LOS (Total LOS/Total Flight Hours) at each Test Condition

was expected since the traffic complexity becomes more constraining on the conflict resolution algorithms as density increases and, hence, solutions are more sensitive to the influence of wind-prediction errors and trajectory modeling errors of actually flown trajectories. Many of these losses corresponded to very small intrusions, (less than 0.05 nmi). The separation minimum for this experiment was set to the en route standard separation of 5.0 nmi. No additional buffers were used to compensate for turn modeling uncertainty (known to be approximately 0.1 nmi) since the goal of this study was to actually determine the requisite value of the separation buffers. Earlier SPAS studies [5] used a 5.1 nmi separation minimum, corresponding to an additional buffer of 0.1 nmi.

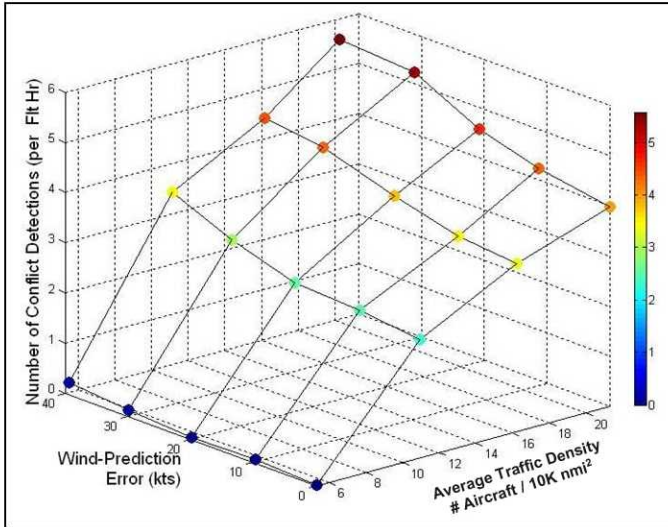


Figure 4. - Number of Conflicts per Flight Hour

For each wind condition, the mean and standard deviation of the wind-prediction error for each aircraft was computed as the average over its entire route (inside the test area) sampled 10 times per second. The results verified that the wind-prediction errors experienced by the aircraft during the test were as intended. Also, both the cross and head (/tail) wind

components were computed to observe their individual effect on resulting LOS. No correlation was observed between the cross and head (/tail) wind errors and the magnitude of the LOS.

The number of conflicts per flight hour is shown in Fig. 4. It is clear that, although that data is nearly the same value for all wind-prediction errors, it also climbs nearly linearly with respect to air traffic density. This indicates that the number of conflicts per flight hour is nearly independent of wind-prediction error (over the range tested), while fully responsive, linearly, with respect to aircraft density. Therefore, even though the number of conflicts increases with density, as expected, it does not vary significantly with respect to wind-prediction error over the range of wind-predictions errors tested. Consequently, this metric would not provide a good basis for estimation of separation buffers for wind-prediction error compensation.

A number of other metrics collected during the experiment seem to have a significant correlation with wind-prediction errors such as secondary conflicts and delayed conflict detections. These metrics will be reported in a later study as they mainly address the performance of the ASAS application and are not central to the objective of this paper.

E. Closest Point of Approach and Losses of Separation

The main metric of interest in this study is the distance at the CPA observed for the traffic densities and wind-prediction error conditions of the experiment. This metric represents the magnitude of the intrusions and will be used to estimate the required additional separation buffers necessary to preserve safe separation. Both metrics, the number of LOS observed, and the distance at the closest point of approach (CPA) for each

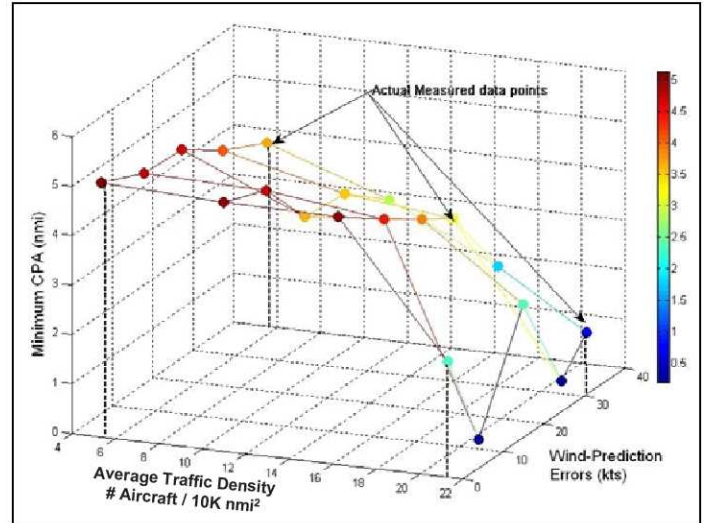


Figure 5. Minimum CPA calculated for each Test Condition

LOS was computed during post processing of time correlated aircraft states. The minimum of those minimum separation distances is the CPA metric used in the study; i.e. the CPA metric is minimum value of all CPAs of each aircraft pair in a simulation for each simulation condition. For replicated runs, this number was calculated as the minimum of the minimums

over all replications. Fig. 5 shows the actual calculated minimum for each condition run. The data for the extreme density case do not exhibit a trend and are not consistent. This is an indicator that the complexity limits for the solution space for the strategic AOP resolution logic under these test conditions has been reached. Since only lateral conflict resolutions are used which are limited to only three types (path stretch, path offset, and path intercept) and forced to comply with an RTA, it is expected that further enhancements to the genetic conflict resolution algorithm [8], introduction of vertical resolutions and constraint relaxation may help overcome this limit. The CPA metric as computed in this experiment was purposefully designed to capture the worst-case observation. Since in this experiment only the intent based, strategic conflict detection and resolution was exercised, it is likely that when the tactical capabilities of AOP are used, some of the LOS would have been prevented or the magnitude of the intrusions reduced. In addition, the strategic resolutions were RTA constrained throughout all the conditions, further increasing the complexity of the test.

The AOP constraint relaxation capability might have prevented some of the LOS resulting from very constrained multi-aircraft conflicts. However, as shown in Figure 5, CPAs show a clear trend as a response function of both traffic density and wind-prediction error for density levels no higher than 16.4. The data at the highest average traffic level indicates that under the conditions of the experiment, the complexity of the traffic is confounding the wind-prediction error effects and cannot be used in calculating an estimate for separation buffers for wind-prediction error compensation. At that level of density-induced complexity, we observe losses of separations that are due to complex multi-aircraft conflicts where strategic resolutions eventually fail to converge. This is an issue to be studied in future experiments that will include tactical CD&R and constraint relaxation methods in order to increase the traffic density levels. However, Fig. 3 and 5 both indicate a clear trend proportional to the magnitude of the wind errors and the traffic density up through 16.

A detailed analysis of the causes and underlying conditions behind the observed LOS, the type of conflicts and resolution strategies, false and missed alerts, as well as the analysis of the trajectory prediction function performance is beyond the scope of this paper. That analysis will be included on an AOP performance study in the near future. In this paper, the primary objective was to analyze the aggregate CPA response to try to infer an estimate for a reasonable separation buffer for wind-prediction error compensation.

V. CPA BUILDING A PREDICTIVE MODEL

While the CPA observations shown in Fig. 5 seem to indicate a trend, it is important to understand how the two factors, traffic density (T) and wind-prediction error (W), affect the response variable (CPA) if we are going to use it to estimate a separation buffer size. A model was built using the experimental design tool Design Expert™ [18]. In this case, a quadratic Response Surface model was used to fit the data shown in Fig. 5. The ranges of the two factors, T and W as well as the response variable are shown in Table II.

TABLE II. DESIGN SPACE RANGES

Name		Range (units)	Mean	Std Dev
T	Factor	5.00-22.00 (count)	8.17	2.16
W	Factor	0-40 (kts)	30	21.21
CPA	Response	0.19-5.13 (nmi)	3.31	1.55

Initial evaluation of measured data showed a strong negative correlation between traffic density and CPA (-0.717) and a moderate positive correlation between wind-prediction errors and CPA (0.453).

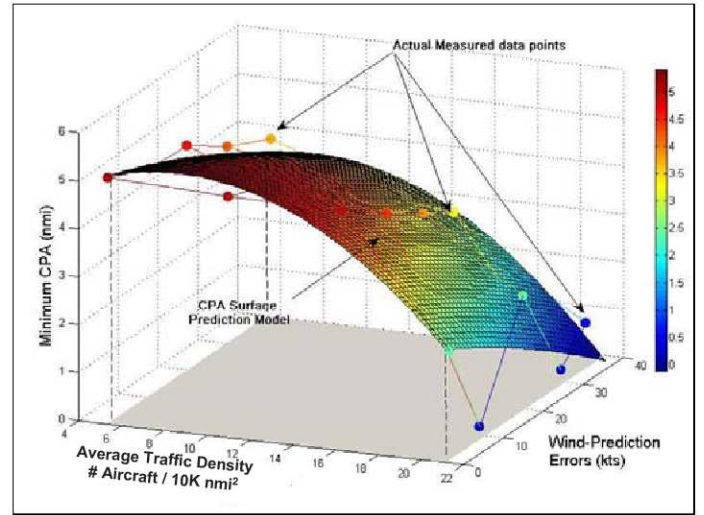


Figure 6. Minimum CPA Surface Model

Figure 6 is a plot of the CPA surface model and the actual minimum CPA data points (Fig. 5) calculated from the experiment. This figure shows the observed minimum CPAs as dots above and below the surface. Note the degradation of the fit at the extreme density. This was discussed in Section IV.D and is due to the inability of the AOP to handle the complexity of this condition within the current constraints imposed on the algorithm. This represents approximately 12 times today's traffic density and is beyond the design requirements specified by NextGen of 2025.

The equation used to model the CPA surface in Fig.6 is given below:

$$CPA = 3.90780 + 0.3409 T - 0.024044 W - 1.15105E-003 TW - 0.019570 T^2 - 3.38857E-004 W^2 \quad (1)$$

The results from an Analysis of Variance (ANOVA) performed on the model are shown in Table III. The significance of each term in the model equation is indicated by the values for "Prob > F". The model was found to be significant with F-value=15.17 and p-value<0.0001. There is only a 0.01% chance that a "Model F-Value" this large could

occur due to noise. F-values less than 0.0500 indicate model terms that are significant. In this case T, W, T^2 are significant model terms. F-values greater than 0.1000 indicate the model terms are not significant. In this case TW and W^2 were found not to be significant. In other words, changes to these two factors would not result in large effects on the response value. The relative significance of the model terms is reflected in the magnitudes of the coefficients in equation (1).

TABLE III. RESULTS FROM DESIGN EXPERT™ ANOVA OF THE CPA MODEL

Source	F-Value	Prob > F
Model	15.17	< 0.0001
T	17.73	0.0009
W	5.03	0.0416
TW	0.32	0.5787
T^2	10.03	0.0069
W^2	0.12	0.7346

Results of further analysis of the significance of the model coefficients are shown in Table IV. The relative impact of the model coefficients can be directly compared in this table since they are expressed in normalized units. The standard error is the estimated standard deviation of the coefficient estimate. The values for lower and upper 95% confidence intervals are shown in the last two columns of Table IV. If the range of the confidence interval includes zero then the coefficient is not significantly different from zero and may not be having a statistically significant effect on the response. This occurs for both the TW and W^2 terms, indicating they may not be significant. At the very least, these confidence values indicate the coefficients for these terms may be poorly estimated.

TABLE IV. RESULTS FROM DESIGN EXPERT™ MODEL COEFFICIENT ANALYSIS

Factor	Coefficient Estimate	Standard Error	95% CI Low	95% CI High
Intercept	-2.77	1.17	-5.27	-0.26
T	-17.06	4.05	-25.76	-8.37
W	-1.39	0.62	-2.71	-0.060
TW	-0.52	0.91	-2.47	1.44
T^2	-9.91	3.13	-16.62	-3.20
W^2	-0.14	0.39	-0.98	0.70

This model can be used as a predictive tool to estimate the size of the separation buffers. It is also a valuable tool to explore the design space to begin to understand the valid ranges of the model factors, beyond which the solution is not valid. For example, the model indicates that the main effect of the density factor at its maximum level (21) is not a good predictor of performance. There are at least two observations that can be made regarding this effect. First, the highest tested density introduces a level of complexity to the scenario that confounds the winds effect. In other words, we cannot infer from the CPA value whether the LOS were the result of aircraft position uncertainty due to wind-prediction errors or too many multi-aircraft conflicts that were too complex to solve strategically.

Second, the CPA minimum value depends on the separation m being used (i.e. 5 nmi). Hence, response values too close to zero are not very reliable.

VI. ANALYSIS OF RESULTS

This section presents an analysis of the results based on the predictive model described in the previous section, and develops an estimate for a reasonable separation buffer for wind-prediction error compensation in ASAS.

The graph in Fig. 7 shows the surface model intersected by planes at boundaries of the design space for which the indicated separation buffers are shown by the contour projection on the horizontal plane. For instance, the bottom plane at Minimum CPA = 2 (intrusion of 3 nmi) indicates that a three nmi buffer (5 nmi separation – 2 nmi CPA) is sufficient to prevent LOS for the factor ranges within the contour labeled “CPA 3 nmi buffer threshold.” In other words, the lowest plane shows the boundary of the “qualifying data” e.g. the maximum ranges of the T and W factors for which the model appears reliable.

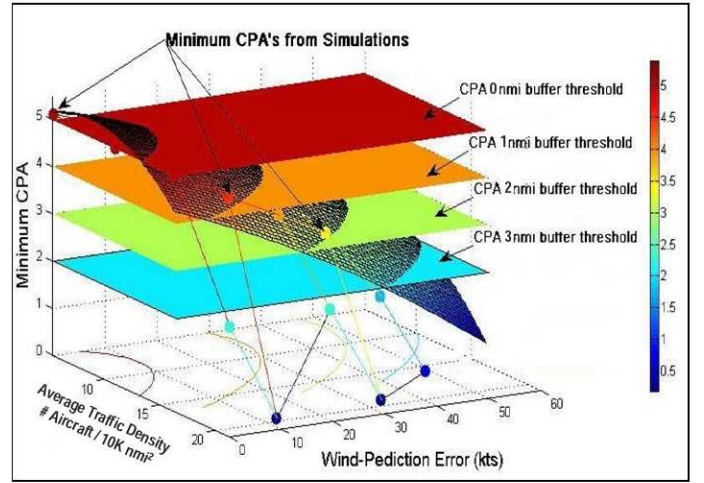


Figure 7: CPA Model and Estimated Separation Buffers

Another view of the estimated separation buffers is provided by the transformed CPA response as shown in (2). The estimated buffer, B, is computed as the ceiling of the separation minimum (M) minus the computed CPA. This equation computes the minimum, integer buffer size required to compensate for the minimum measured CPA. In this experiment, the value of the separation minimum M is 5 nmi, hence the transformed response was computed by the expression in (3).

$$B = \lceil (M - CPA) \rceil \quad (2)$$

$$B = \lceil (5 - CPA) \rceil \quad (3)$$

The contour graph in Fig. 8 is the horizontal projection of the buffer response surface shown in Fig. 7, in which the design points (Fig. 5) are shown as dots. The color intensity of both the contours and the data points indicate the value of

minimum CPA. The horizontal axis displays the traffic density T over a range of five to 16 aircraft per 10K nmi², excluding the highest level of the factor. The vertical axis displays the wind-prediction error W over a range of zero to 60 kts, extending the design space beyond the measured range. The contour lines indicate estimated buffer sizes in nmi (identified by the numbered squares) corresponding to the different levels of the factors T and W . The use of predictive models outside the design space is acceptable in this case since these are exploratory results to be used in upcoming validation studies.

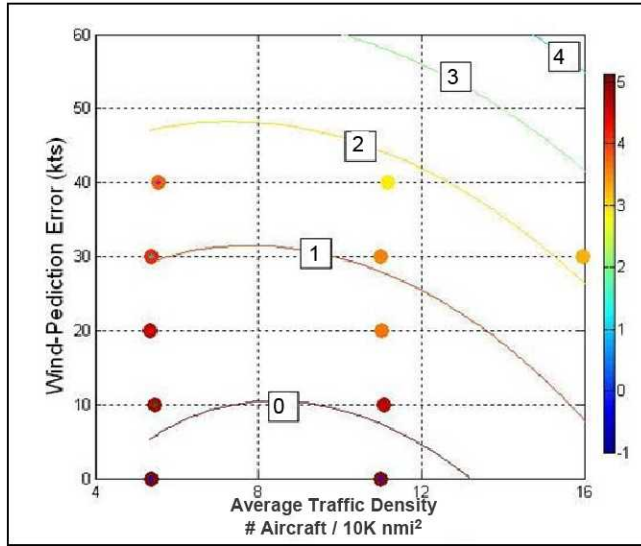


Figure 8: Contour graph of the buffer size model

VII. COMPARISON OF VARYING TRUTH VS PREDICTED WINDS IN ASSESSING WIND-PREDICTION ERROR

A set of runs was conducted at a single average traffic density of approximately 10 aircraft per 10K nmi² in which the predicted winds were varied while the truth winds were held constant.

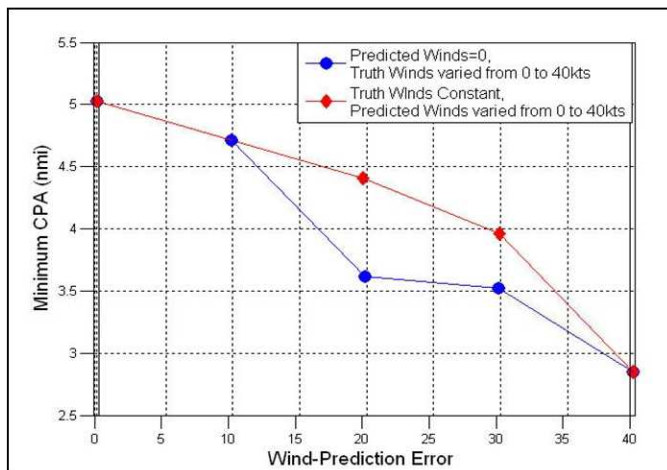


Figure 9. Comparison of minimum CPA resulting from varying predicted winds vs. truth winds

In these runs the truth winds were set to zero kts and the predicted wind speed was varied from 10 to 40 kts. These runs were conducted in order to determine whether there is a significant difference in the ASAS algorithm performance if wind error results primarily from poor prediction in the presence of winds versus over-prediction of winds when there are no winds.

Fig. 9 shows the minimum CPA results from these runs. Based on this one sample of runs, it appears that results are different. More research needs to be conducted to determine both the reasons for and the significance of these differences. However, based on these results, the current buffer estimates appear to be adequate in that they work for both cases.

VIII. CONCLUSIONS AND FUTURE WORK

The primary goal of this experiment was to estimate the separation buffer size required to compensate for wind prediction error in an Airborne Separation Assistance System. Results suggest that the strategic airborne separation functions exercised in this experiment can sustain wind prediction errors up to 40kts at current day air traffic density with no additional separation distance buffer and at eight times the current day with no more than a 60% increase in separation distance buffer.

An experimental model for separation buffer estimation was developed to characterize the data. It was shown that this model could be used to determine an estimate to meet the goals of this study. The constructed model can also be used to continue the exploration of safety performance of automated separation tools in the presence of wind-prediction errors. A methodology in building a predictive model was developed that can be used to explore the effects of other sources of error and system degradation and human performance in order to mitigate system uncertainties in automated separation tools. This research will continue with the testing and validation of the estimated buffers reported in this paper in upcoming safety evaluation experiments under similar simulation conditions.

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